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MARCH 15, 1993

TOOL LIFE

ANALYSIS AND FORECASTING: 2

FORECASTING TOOL LIFE USING NEURAL NETWORKS

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TO ACHIEVE SEMI-UNTENDED OR UNTENDED MACHINE OPERATION IN A FACTORY ENVIRONMENT FORECASTING TOOL LIFE IS A PREREQUISITE. IN ORDER TO ACHIEVE THIS ROCK ISLAND ARSENAL INITIATED A TOOL LIFE TEST PROGRAM FOR 3/4 INCH DRILLS. AMCCOM SYSTEMS ANALYSIS OFFICE HAS STATISTICALLY ANALYZED THIS DATA AND EMPLOYED IN THE DEVELOPMENT OF A NEURAL NETWORK CAPABLE OF FORECASTING TOOL LIFE. IT HAS BEEN SHOWN THAT A NETWORK HAS THIS CAPABILITY TO FORECAST TOOL LIFE BASED ON THE AVERAGE THRUST VALUES PER WORKPIECE FOR THE FIRST NINE WORKPEICES.

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1. **SUMMARY:**

The Rock Island Arsenal Operation Directorate is evolving into a Flexible Computer Integrated Manufacturing (FCIM) facility. The FCIM enhances production diversity. But, full FCIM benefits can only be achieved in facilities capable of untended or semi-untended operations. However, this capability creates tool replacement problems. In a one-operator-one-machine environment the operator is always in the vicinity of the machine and can receive sensory signals (aural, visual, olfactory, or tactile) from a worn tool and replace it before the workpiece is damaged. But, in untended or semi-untended operations the operator might not be in the vicinity to receive the tool's signal, resulting in a ruined workpiece.

The Rock Island Arsenal solution to this problem is to forecast tool life, monitor current tool age (inches drilled, workpieces completed, tool lip wear) and when current tool age is within some range of forecasted tool life the operator is notified. The operator then orders a replacement tool and has it available for immediate replacement when current age equals forecasted tool life. This eliminates the possibility of the tool wearing out and ruining the workpiece and it alleviates the wait while a tool is brought to the machine from the tool crib.

Implementation of this solution is contingent on the capability to forecast tool life. Tool life can be forecast in millimeters of drill lip wear, linear inches of metal drilled, or workpieces completed. Tool lip wear is the primary indicator. However, monitoring lip wear requires that either a wear sensor be incorporated into the machine to dynamically measure lip wear or the wear has to be manually measured after each workpiece is completed. The first option increases the cost and complexity of the machine and the second option decreases productivity. These monitoring complications can be circumvented by forecasting tool life in either total inches drilled or workpieces completed, both of which are easy to monitor. Either variables can: (1) be forecasted directly, (2) can be derived by forecasting wear and wear rate (millimeters of wear per inch of metal drilled or millimeters of wear per workpiece) and dividing wear by wear rate; or (3) can be derived by choosing a constant wear value, such as the mean wear for all tested drills, and using this value in conjunction with a forecasted wear rate to forecast tool life.

To develop a forecasting capability Rock Island Arsenal initiated an experimental program to gather the data necessary for the development of a forecasting method. The experiments are being conducted by Dr. J. L. Moriarty --of the Rock Island Arsenal Science and Engineering Directorate. The set of three-quarter inch experimental drills consists of: (1) new drills with a conventional grind (2) reground drills with a conventional grind (3) reground drills with a four facet grind (4) reground drills with a helical grind. The experiments are being conducted within a manufacturing instead of a laboratory

environment. Because of this the drills cannot be allowed to fail and ruin the workpieces (a component of the M1A1 tank's main gun), they must be removed prior to failure. Drill removal is at the discretion of the machine operator, whose removal decision is based on sensory signals given off by the drill.

The objective of the current effort is to prove the feasibility of using neural networks to forecast the life of three-quarter inch drills used on a component of a M1A1 tank's main gun. However, data was gathered on many tool parameters so this effort also included a statistical analysis of the data. This was included primarily to establish an understanding of the working phenomena that might be useful in the development of a neural network. The statistical analysis was conducted prior to the neural network activity and is the subject of a companion report. The neural network investigation is the subject of this report.

The feasibility of using one or more neural networks to forecast tool life was determined by developing neural networks and testing them for forecast accuracy. Development and test was carried out using NETS. The NETS is a neural network simulation computer program developed by National Aeronautics and Space Agency (NASA). The NETS simulates feed-forward, back-propagation neural networks.

The first set of neural networks, developed to forecast tool life, used values of the descriptive parameters, listed in Table 1.0, as the independent variables. This was attempted even though the prior statistical analysis showed that there is little correlation between these parameters and tool life. When this approach did not prove fruitful two more independent variables were added: first workpiece minimum thrust (measured at the ball screw motor as a percent of maximum thrust the motor is capable of providing) and first workpiece specific energy (measured at the spindle motor as horsepower provided by the motor divided by the quotient of the cubic inches drilled and the feed rate-hp/(cu.in./min.)). The reason for including these variables was that it was hypothesized that the values for the first piece might be a measure of a drill wear-in. Different values would account for differences in drill hardness. This excursion also failed. In another attempt the descriptive parameter values were combined with a series of dynamic parameter values, either thrust or specific energy). For these attempts the average thrust or specific energy value per workpiece for the first five workpieces was used. This additional information did not improve the networks forecasting capability. Therefore, the use of descriptive variables was terminated and attention was focused on the dynamic variables. The final result of the experimentation was a decision to use the average thrust per workpiece for the first 9 workpieces as the independent variable and total inches drilled per twist drill as the dependent variable. It was decided to use inches drilled instead of workpieces completed as the dependent variables in case the

results have a more general application to other drill and workpiece combinations.

Based on the results of this effort it is concluded that neural networks can be developed with the capability of forecasting tool life. However, for this study the amount of available data was insufficient to both train and test a network. To achieve sufficient accuracy all of the available data was used in the training set for the last network that was developed. However, the test program is continuing and as more data is generated the neural networks will be updated.

2. DATA:

Characteristic drill and workpiece variables are listed in Table 1.0 and the relationship between the drill variables and drill geometry are shown in Figure 1.0. Data was collected on: the first thirteen variables. In addition, data was collected on: (1) tool life (inches drilled, workpieces completed, and tool lip wear), (2) thrust--percent of maximum d.c. current required by the ball screw motor-- (3) specific energy (hp/(cu.in./min.)) provided by the spindle motor to turn the drill. The dynamic parameter data, thrust and specific energy, were collected every tenth of an inch drilled. For each workpiece 9.3 inches were drilled: 8 inches for four 2 inch through holes and an additional 1.3 inches for 2 blind holes. However, since there was little variation in the data per measurement or average per hole an average per workpiece (9.3 inches) was used.

The descriptive variable values are shown in Tables 2.0 - 5.0. The data for 25 new drills (23 manufacturer A and 2 manufacturer B) are shown in Table 2.0. Data for 27 reground drills (22 A and 5 B) with a conventional grind are presented in Table 3.0. Data for 18 reground drills with a four faceted grind are shown in Table 4.0 and Table 5.0 is for 2 reground helical grind drills. The drills in these last two tables are all 'A' drills. Regrinding was done by in-house machinists. Tables 6.0-9.0 contain performance data: inches drilled, workpieces, total wear (millimeters) and wear rate (millimeters/inch). Total wear was measured after the operator judged that the tool had reached the end of its useful life and removed it from the machine. Measurements were taken directly from photos of the dull drill points. The constant wear rate was calculated from total wear and inches drilled.

There are 25 new drills of which 23 are from the same manufacturer. The analysis of drill variables; point angle, relief angle, etc. are limited to 22 of these 23 drills unless otherwise noted.

TABLE 1.0

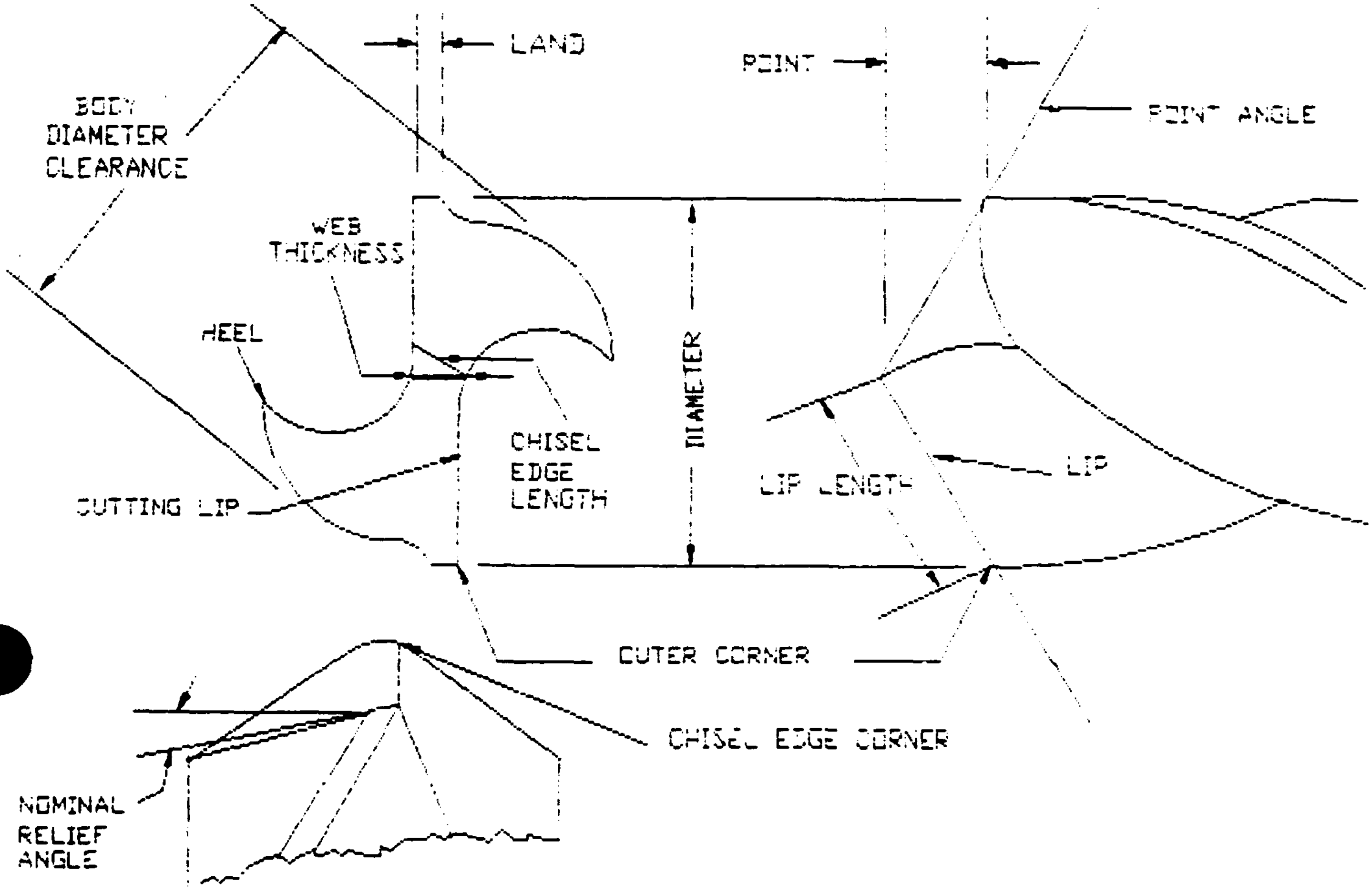
CHARACTERISTIC VARIABLES

1. POINT ANGLE
2. RELIEF ANGLE
3. CHISEL EDGE LENGTH
4. WEB THICKNESS
5. DRILL SURFACE TREATED OR UNTREATED
6. CRYOGENIC TREATMENT
7. ION IMPLANTATION SURFACE TREATMENT
8. LOW, MEDIUM, OR HIGH ION FLUX
9. DRILL COATED OR NOT COATED WITH TiN
10. DRILL MANUFACTURERS-2
11. DRILL NEW OR REGROUND
12. TYPE OF GRIND-CONVENTIONAL, HELICAL, FOUR FACET
13. DRILL STRESS RELIEVED OR NOT
14. DRILL HARDNESS
15. WORKPIECE HARDNESS

TABLE 2.0

NEW DRILL DESCRIPTIVE DATA
CONVENTIONAL POINT GRIND

TEST SEQ.	MFG.	PT. ANGLE	RELIEF ANGLE	CEL	WEB	CEL/WEB	CRYO TRTD	ION TRTD	FLUX LEVEL	TiN CTD
1	A	118	10	.050	.042	1.190	NO	NO	N/A	YES
6	A	118	10	.056	.045	1.240	NO	NO	N/A	YES
9	A	118	10	.062	.051	1.220	YES	NO	N/A	YES
10	A	118	10	.068	.056	1.210	YES	NO	N/A	YES
11	B	118	8	.110	.099	1.110	NO	NO	N/A	YES
12	B	118	8	.110	.099	1.110	NO	NO	N/A	YES
13	A	118	10	.050	.042	1.190	YES	NO	N/A	YES
17	A	120	8	.072	.065	1.150	NO	NO	N/A	YES
20	A	122	10	.069	.061	1.130	NO	NO	N/A	YES
26	A	120	11	.088	.076	1.160	NO	NO	N/A	YES
27	A	120	10	.062	.053	1.170	NO	NO	N/A	YES
28	A	120	11	.041	.034	1.210	NO	NO	N/A	YES



DRILL GEOMETRY
FIGURE 1.0

33	A	120	11	.054	.047	1.150	NO	NO	N/A	YES
38	A	118	10	.062	.054	1.150	NO	NO	N/A	YES
58	A	120	8	.072	.065	1.150	NO	YES	LOW	YES
61	A	120	6	.059	.051	1.160	NO	YES	HIGH	YES
62	A	120	4	.063	.055	1.150	NO	YES	MED	YES
63	A	118	4	.068	.054	1.260	NO	NO	N/A	YES
67	A	122	4	.053	.044	1.200	NO	NO	N/A	YES
71	A	124	4	.053	.045	1.180	NO	NO	N/A	YES
79	A	122	10	.072	.062	1.160	NO	YES	MED	YES
80	A	122	8	.071	.063	1.130	NO	YES	MED	YES
81	A	122	8	.072	.062	1.160	NO	YES	MED	YES
83	A	120	8	.075	.065	1.150	NO	NO	N/A	YES
91*	A	122	7	.052	.045	1.156	NO	NO	N/A	YES

*NOT USED IN STATISTICAL ANALYSIS AND SOME NEURAL NETWORKS BECAUSE ANALYSIS WAS COMPLETED BEFORE TESTING WAS COMPLETED.

MFG = MANUFACTURER
A = GUHRING
B = PTD
PT = POINT
CEL = CHISEL EDGE LENGTH IN INCHES
WEB = WEB THICKNESS IN INCHES

TABLE 3.0

REGROUND DRILLS DESCRIPTIVE DATA
CONVENTIONAL POINT GRIND

TEST SEQ.	MFG.	PT. ANGLE	RELIEF ANGLE	CEL	WEB	CEL/WEB	CRYO TRTD	ION TRTD	FLUX LVL	TiN CTD	STRESS RELIEF
4	A	120	7	.143	.113	1.270	NO	NO	N/A	NO	NO
5	A	118	9	.063	.052	1.210	NO	NO	N/A	NO	NO
7	A	118	4	.044	.041	1.070	NO	NO	N/A	NO	NO
8	A	118	7	.075	.069	1.090	NO	NO	N/A	NO	NO
16	B	118	7	.062	.053	1.170	NO	NO	N/A	NO	NO

18	A	120	6	.059	.053	1.110	NO	NO	N/A	NO	NO
22	A	120	8	.062	.038	1.630	NO	NO	N/A	NO	NO
24	A	120	5	.053	.045	1.180	NO	NO	N/A	NO	NO
29	A	120	10	.042	.037	1.300	NO	NO	N/A	NO	NO
30	A	120	10	.046	.040	1.150	NO	NO	N/A	NO	NO
31	A	120	12	.042	.030	1.400	NO	NO	N/A	NO	NO
32	A	124	12	.048	.037	1.300	NO	NO	N/A	NO	NO
34	A	120	10	.035	.031	1.130	NO	NO	N/A	NO	NO
36	A	120	11	.071	.050	1.420	NO	NO	N/A	NO	NO
39	A	116	12	.053	.048	1.100	NO	NO	N/A	NO	NO
45	A	122	14	.044	.025	1.760	NO	NO	N/A	NO	NO
50	B	120	9	.044	.035	1.260	NO	NO	N/A	NO	NO
51	B	120	8	.044	.035	1.260	NO	NO	N/A	NO	NO
52	A	120	5	.069	.058	1.190	NO	NO	N/A	NO	NO
54	A	118	4	.040	.034	1.180	NO	NO	N/A	NO	NO
55	A	120	4	.094	.067	1.400	NO	NO	N/A	NO	NO
64	A	120	6	.069	.054	1.290	NO	NO	N/A	NO	YES
66	A	120	7	.063	.048	1.310	NO	NO	N/A	NO	YES
70	B	122	5	.125	.099	1.260	NO	NO	N/A	NO	NO
82	A	120	5	.066	.051	1.290	NO	NO	N/A	YES	NO
85	B	120	5	.058	.047	1.230	NO	NO	N/A	YES	NO
87	A	120	5	.072	.058	1.240	NO	NO	N/A	YES	NO

STRESS RELIEF = A NON-HEAT TREATMENT

TABLE 4.0

REGROUND DRILLS DESCRIPTIVE DATA
FOUR FACETED POINT GRIND

TEST SEQ	MFG	PT. ANGLE	RELIEF ANGLE	CEL	WEB	CEL/WEB	CRYO TRTD	ION TRTD	FLUX LVL	TiN CTD	STRESS RELIEF
30	A	118	11	.016	.012	1.330	NO	NO	N/A	NO	NO
40	A	120	13	.016	.014	1.140	NO	NO	N/A	NO	NO
53	A	120	6	.056	.048	1.170	NO	NO	N/A	NO	NO
56	A	123	9	.056	.047	1.190	NO	NO	N/A	NO	NO
57	A	118	5	.047	.033	1.420	NO	NO	N/A	NO	NO
59	A	118	8	.094	.075	1.250	NO	NO	N/A	NO	NO
72	A	122	7	.025	.019	1.320	NO	NO	N/A	NO	NO
73	A	122	5	.100	.071	1.410	NO	NO	N/A	NO	NO
74	A	120	5	.069	.052	1.330	NO	NO	N/A	NO	NO
75	A	124	5	.019	.014	1.360	NO	NO	N/A	NO	NO
77	A	122	6	.022	.015	1.470	NO	NO	N/A	NO	NO
84	A	120	5	.016	.013	1.230	NO	NO	N/A	YES	NO
86	A	120	5	.010	.008	1.250	NO	NO	N/A	YES	NO
88	A	122	6	.016	.013	1.230	NO	NO	N/A	YES	NO
89*	A	120	5	.022	.017	1.290	NO	NO	N/A	NO	NO
90*	A	120	5	.014	.011	1.270	NO	NO	N/A	NO	NO
92*	A	124	7	.025	.020	1.250	NO	NO	N/A	NO	NO
93*	A	124	6	.020	.015	1.330	NO	NO	N/A	NO	NO

*NOT USED IN STATISTICAL ANALYSIS AND SOME NEURAL NETWORKS BECAUSE ANALYSIS WAS COMPLETED BEFORE TESTING WAS COMPLETED.

TABLE 5.0
REGROUND DRILLS DESCRIPTIVE DATA
HELICAL POINT GRIND

TEST SEQ	MFG	PT. ANGLE	RELIEF ANGLE	CEL	WEB	CEL/WEB	CRYO TRTD	ION TRTD	FLUX LVL	TiN CTD	STRESS RELIEF
68	G	122	5	.119	.104	1.140	NO	NO	N/A	NO	NO
69	G	122	5	.126	.113	1.120	NO	NO	N/A	NO	NO

TABLE 6.0

NEW DRILLS PERFORMANCE DATA
CONVENTIONAL POINT GRIND

TEST SEQ	TOOL LIFE INCHES DRILLED	TOOL LIFE TOTAL WEAR MM	WEAR RATE MM/INCH	TOOL LIFE WORKPIECES
1	204.6	.31	.00152	22
6	241.8	.34	.00141	26
9	213.9	.27	.00126	23
10	167.4	.21	.00125	18
11	260.4	.28	.00107	28
12	269.7	.28	.00104	29
13	279.0	.31	.00111	30
17	446.4	.34	.00076	48
20	390.6	.31	.00079	42
26	204.6	UNK	UNK	22
27	260.4	.28	.00108	28
28	241.8	.31	.00128	26
33	288.3	.30	.00104	31
38	306.9	.30	.00098	33
58	474.3	.39	.00082	51
61	344.1	.31	.00090	37
62	195.3	.28	.00143	21
63	204.6	.25	.001[illegible]	22
67	158.1	.31	.00196	17
71	316.2	.28	.00088	34
79	241.8	.28	.00116	26
80	139.5	.22	.00158	15
81	241.8	.32	.00132	26
83	325.5	.25	.00077	35
91	465.0	.31	.00067	50

UNK = TOTAL WEAR WAS NOT MEASURED FOR THIS DRILL

TABLE 7.0

REGROUND DRILLS PERFORMANCE DATA
CONVENTIONAL POINT GRIND

TEST SEQ	TOOL LIFE INCHES DRILLED	TOOL LIFE TOTAL WEAR MM	WEAR RATE MM/INCH	TOOL LIFE WORKPIECES
4	65.1	.16	.00245	7
5	65.1	.13	.00199	7
7	102.1	.16	.00156	11
8	167.4	.28	.00167	18
16	65.1	.16	.00245	7
18	223.2	.37	.00165	24
22	148.8	.27	.00181	16
24	55.8	.17	.00304	6
29	93.0	UNK	UNK	10
30	176.7	.39	.00220	19
31	139.5	UNK	UNK	15
32	83.7	UNK	UNK	9
34	186.0	.33	.00177	20
36	120.9	UNK	UNK	13
39	167.4	.25	.00149	18
45	148.8	.28	.00188	16
50	102.3	.23	.00224	11
51	297.6	.39	.00131	32
52	83.7	.23	.00274	9
54	120.9	.28	.00231	13
55	55.8	.15	.00268	6
64	158.1	.31	.00196	17
66	46.5	.18	.00387	5
70	241.8	.23	.00095	26
82	353.4	.39	.00110	38
85	306.9	.28	.00091	33
87	334.8	.34	.00102	36

TABLE 8.0

REGROUND DRILLS PERFORMANCE DATA
FOUR FACETED POINT GRIND

TEST SEQ	TOOL LIFE INCHES DRILLED	TOOL LIFE TOTAL WEAR MM	WEAR RATE MM/INCH	TOOL LIFE WORKPIECES
37	139.5	.17	.00121	15
40	316.2	.44	.00139	34
53	288.3	.39	.00135	31
56	83.7	.23	.00274	9
57	186.0	.39	.00209	20
59	204.6	.39	.00190	22
72	139.5	.23	.00164	15
73	102.3	.13	.00127	11
74	120.9	.23	.00190	13
75	167.4	.39	.00232	18
77	213.9	.40	.00187	23
84	446.4	.36	.00080	48
86	344.1	.26	.00072	36
88	455.7	.36	.00079	49
89	269.7	.36	.00149	26
90	297.6	.42	.00141	32
92	418.5	.39	.00093	45
93	344.1	.36	.00105	37

TABLE 9.0

REGROUND DRILLS PERFORMANCE DATA
HELICAL POINT GRIND

TEST SEQ	TOOL LIFE INCHES DRILLED	TOOL LIFE TOTAL WEAR MM	WEAR RATE MM/INCH	TOOL LIFE WORKPIECES
68	130.2	.31	.00238	14
69	148.8	.34	.00228	16

3. NEURAL NETWORK:

a. Analysis:

(1) Scaling of Data:

NETS requires that the input and output data be scaled between the theoretical limits of zero and one. These are the theoretical limits; in practice the limits are .1 and .9. To scale the data the minimum and maximum values a reselected from all of the available problem description data (input data) and all available problem solution data (output data). For this

scaling the minimum and maximum values used in the scaling must span the minimum and maximum values that could be realized in a working environment, otherwise it is possible that a problem will be encountered with values outside the scaling range. A possible strength of scaling is that all problems are scaled using the same values thereby creating a relationship between problems. For this study the minimum and maximum values were selected from the values for all tested drills, new and reground.

(2) Training Criteria:

The training criteria value is set by the network developer and it is the maximum error, between the actual answers and the neural network's generated answers for each example in the training set, that the network developer will accept. When the network achieves this value, during training, the training phase is terminated and the test phase can be initiated. The developer can set this criteria at as low a value as is desired, however, improvements in network test case accuracy tends to diminish as the criteria is made smaller, at least for this problem. The accuracy of the solutions for training examples improves but the accuracy for unknown test examples not contained in the training set diminishes. Specific knowledge is gained but generalization capability is lost.

To determine the impact of training criteria on accuracy, for this problem, an experiment was conducted in which the training criteria was set at 14 values. This was done within the context of one training session. The criteria was first set at a high value and the network was trained to this value and then it was tested. Then the training was resumed from the stopping point but with a new lower criteria.

This was continued for 14 training criteria values .5 - .008. For each criteria value the network was first trained and then challenged with the training set (17 out of 20 available manufacturer "A" drills) and then with the remaining 3 unknown manufacturer "A" drills. The minimum and maximum errors for each criteria value for the training set are shown in Figure 2.0, the minimum and maximum errors for each criteria value for the test set are shown in Figure 3.0 and the root mean square error for the training set, test set, and the combined training and test set are shown in Figure 4.0. As the training criteria value is reduced the upper and lower bounds on the prediction error for the training set converge on zero, Figure 2.0. However, for the test set, Figure 3.0, the upper and lower bounds start to converge at a criteria value of approximately .26. But, at a criteria value of .05 the bounds stop converging. This fact is brought out in Figure 4.0 which is a plot of root mean square error. For the test set this parameter flattens out at approximately .05. Therefore, for this effort the training criteria was set at a value of .05.

(3) Objective Criteria:

In a working environment there would be limits on the neural network's decisions. For this investigation it was decided to establish an acceptable error of plus or minus two workpieces or plus or minus 18.6 inches. In addition the minimum acceptable forecast for inches drilled with a new drill was set at 139.5 and the maximum was set at 474.3. These are the minimum and maximum values for the new drills. If a network forecast, a value less than 139.5, the forecast is set to 139.5 and if it forecast a value greater than 474.3 the value is set at 474.3. For reground conventional grind drills the values are 93.0 and 353.4. For reground four facet grind the values are 102.3 and 455.7. Table 10.0 shows the training criteria results.

TABLE 10.0

TRAINING CRITERIA TRAINING SESSION
NUMBER OF FORECASTS BETWEEN
PLUS AND MINUS TWO WORKPIECES

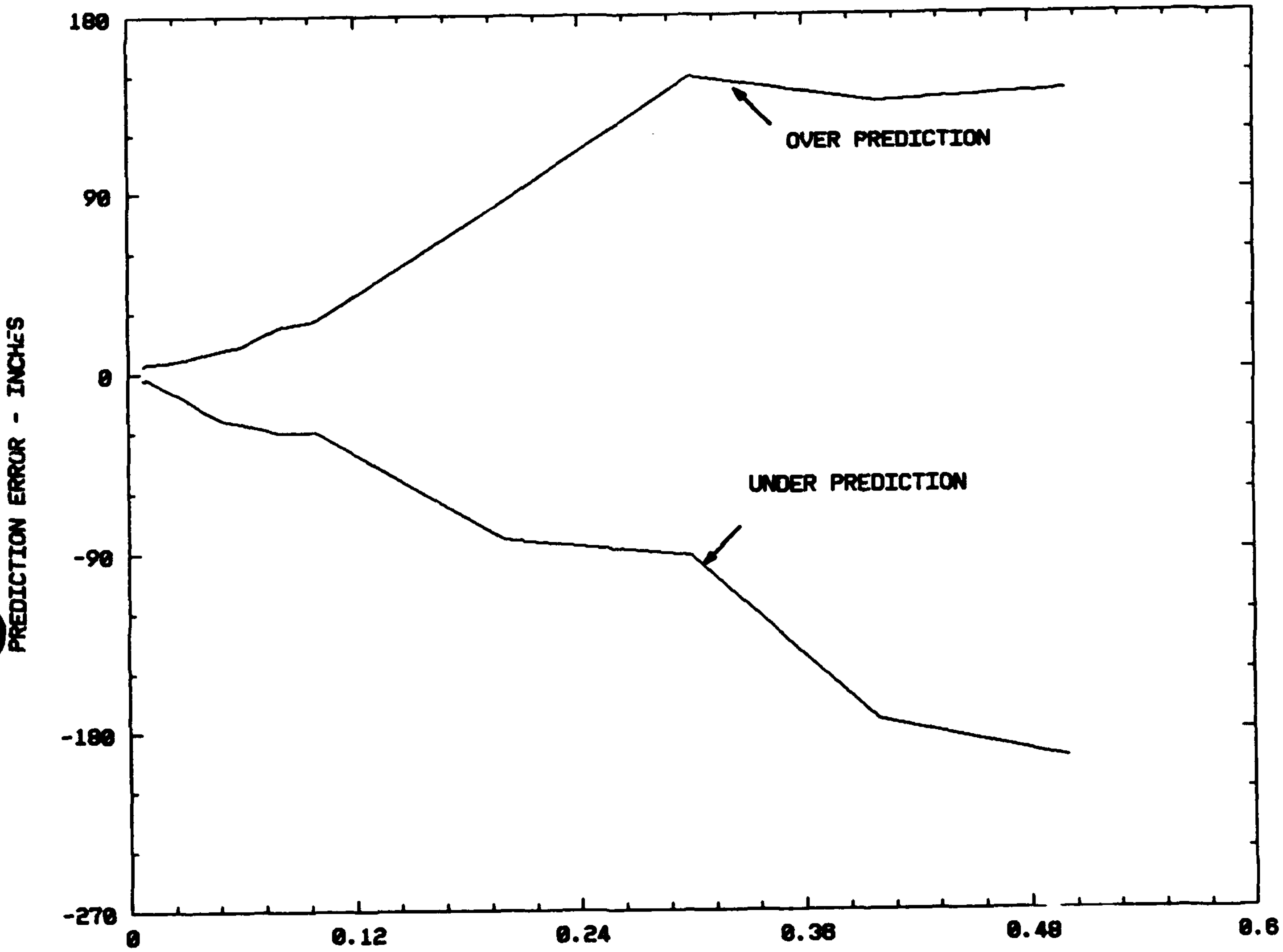
CRITERIA LEVEL	TRAINING SET (17 EXAMPLES)	TEST SET (3 EXAMPLES)
.5	2	0
.4	3	0
.3	4	0
.2	10	0
.1	13	1
.08	12	2
.06	15	2
.05	16	1
.04	16	1
.03	17	1
.02	17	0
.01	17	1
.009	17	1
.008	17	1

(4) Problem Definition:

The dynamic data available for problem definition included the thrust and specific energy (hp/(cu.in./in)). During drilling thrust is measured every tenth of an inch. For specific energy both horsepower and feed rate are measured every tenth of an inch and these values are used to derive specific energy. The thrust measurements are taken at the ball screw motor and the horsepower measurements are taken at the spindle motor. For this effort the independent variables were average thrust and average specific energy per workpiece (9.3 drilling inches).

The thrust and specific energy values were derived for each two inch hole, four holes per workpiece, from the last three

NETWORK LEARNING CRITERIA VS. TRAINING SET PREDICTION ERROR BOUNDS
NUMBER OF EXAMPLES IN TRAINING SET - 17



NETWORK LEARNING CRITERIA
FIGURE 2.0

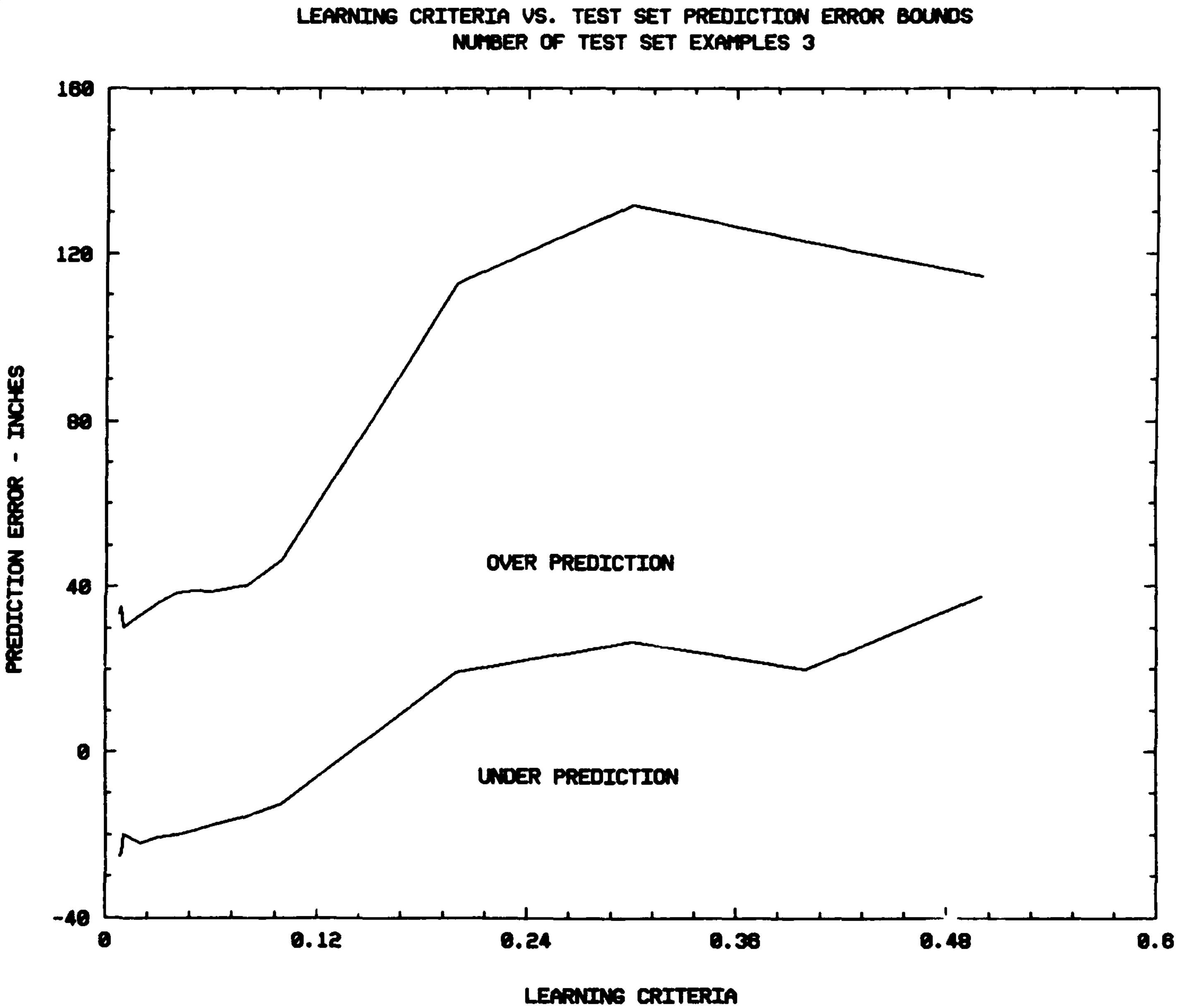

LEARNING CRITERIA VS. TEST SET PREDICTION ERROR BOUNDS
NUMBER OF TEST SET EXAMPLES 3
160
120
80
40
0
-40
0
0.12
0.24
0.36
0.48
0.6
PREDICTION ERROR - INCHES
OVER PREDICTION
UNDER PREDICTION
LEARNING CRITERIA

FIGURE 3.0

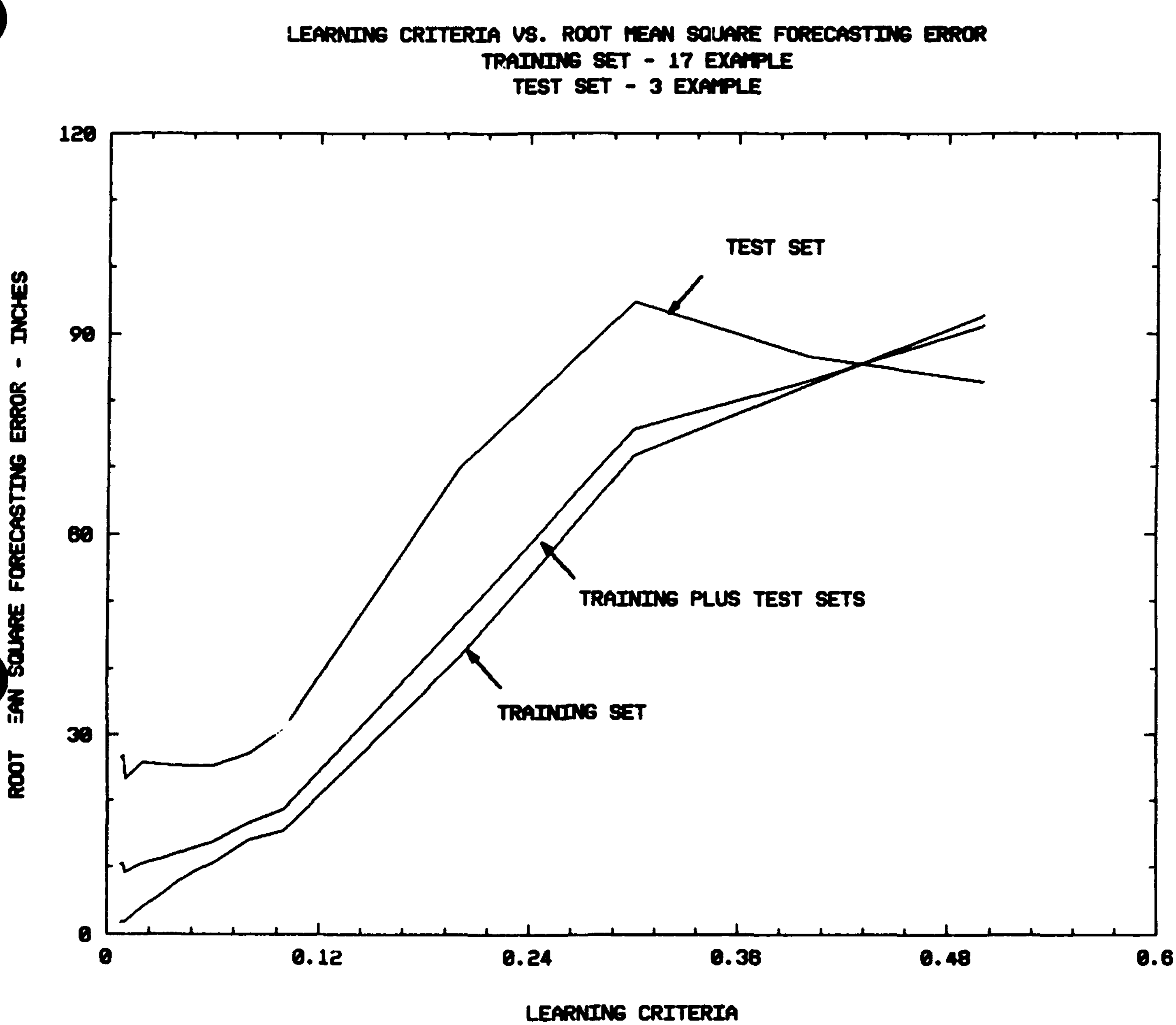

LEARNING CRITERIA VS. ROOT MEAN SQUARE FORECASTING ERROR
TRAINING SET - 17 EXAMPLE
TEST SET - 3 EXAMPLE
TEST SET
TRAINING PLUS TEST SETS
TRAINING SET
120
90
60
30
0
0
0.12
0.24
0.36
0.48
0.6
ROOT MEAN SQUARE FORECASTING ERROR - INCHES
LEARNING CRITERIA

FIGURE 4.0

measurements per hole. These four values were then used to determine a workpiece average. From this data two additional problem definition methods were developed: smoothed and first differences for both average thrust and average specific energy.

Tool life (inches drilled) forecasting networks were trained and tested for each of the problem definition methods. The training set consisted of the 15 new drills from manufacturer "A." The test set consisted of the remaining 6 manufacturer "A" examples. Equation (1) is the smoothing equation and equation (2) is the first difference equation. The smoothing produced problem definition of nine values and the first difference produced problem definition of 7 values. The results are shown in Table 11.0.

(1) $T(i) = T(i-1) + 2T(i) + T(i+1) / 4$

(2) $T(i) = T(i+1) - T(i-1) / 2$

TABLE 11.0
PROBLEM DEFINITION
TRAINING SET = 15 EXAMPLES
TEST SET = 6 EXAMPLES

PARAMETER	RMSE* TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
THRUST	7.2	117.8	15	1
SMOOTHED THRUST	8.32	58.3	15	2
1ST DIFFERENCE THRUST	18.91	159.6	11	0
SPECIFIC ENERGY	15.0	47.72	13	1
SMOOTHED SPECIFIC ENERGY	12.0	88.60	14	1
1ST DIFFERENCE SPECIFIC ENERGY	NETWORK WOULD NOT TRAIN			

* ROOT MEAN SQUARE FORECASTING ERROR

Thrust and smoothed thrust did very well when challenged with the training set, however, neither achieved an acceptable accuracy when challenged with a test set. In fact the best accuracy when challenged with the test set was specific energy, however, it did not do as well in learning the training set. Since none of these approaches fulfilled performance expectations examples were moved from the test set to the training set. This was done in order to increase the neural networks knowledge concerning the span of possible problems. It was hoped that at some training set test set combination the accuracy for both sets would fulfill expectations. This goal was not achieved so it was decided to include all of the examples in the training set. The results for this option are shown in Table 12.0.

TABLE 12.0

PROBLEM DEFINITION
TRAINING SET = 21 EXAMPLES

PARAMETER	RMSE TRAINING SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES
THRUST	8.84	21
SMOOTHED THRUST	15.59	19
SPECIFIC ENERGY	8.37	21
SMOOTHED SPECIFIC ENERGY	11.83	20

This effort resulted in the elimination of both smoothed approaches from further considerations. This was done for two reasons: (1) their performance was not equal to the other approaches, and (2) as the number of examples in the training set increased the capability of the network to converge to the training criterium value became more and more difficult. Since the amount of training examples will increase in the future this convergence difficulty could become more of a problem.

Although specific energy has a slight accuracy advantage over thrust, the RMSE values are both within one workpiece. Because of these results, specific energy was eliminated from further consideration since it requires a more complicated sensing system; it requires that both horsepower and feed rate be monitored; and since it is a quotient, slight changes in either of these variables can have a sizeable impact.

(5) Required Number of Inputs to Define Problem:

The minimum number of workpieces completed by a new drill was fifteen. If each piece provides one data point for problem definition it is possible to use data from up to fourteen workpieces for problem definition. To determine the number of data points that provide the best problem definition neural networks were trained using from five to fifteen data points per problem. Five values networks would not converge to the .05 training criteria. For all of these experiments the training set consisted of 15 examples and the test set consisted of 6 examples. Results are furnished in Table 13.0

TABLE 13.0

NETWORK ACCURACY FORECASTING TOTAL INCHES DRILLED

NUMBER OF AVERAGE THRUST VALUES	RSME TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
5*	N/A	N/A	N/A	N/A
6	15.7	93.7	14	2
7	11.0	83.0	15	1
8	12.2	75.4	14	0
9	7.2	117.8	15	1
10	46.0	88.5	8	1
11	35.0	144.5	8	0
12	39.5	126.5	10	0
13	40.3	151.2	8	1
14	25.9	123.3	11	0
15	27.3	143.7	9	1

* Would not converge.

None of the results for input values of 9 or less is in every respect the best. However, an attempt was made to improve network accuracy by adding training examples to the training set. The additional examples caused the 6 element case to reach a point were the network would not converge. The 7 element case would converge but convergence became difficult. Therefore, it was decided that problem definition would require at least 9 elements.

(6) Number of Training Set Examples:

A rule of thumb for the number of examples to be included in the training set is that it should be 5 to 10 times the number of weights from the input layer to the middle layer. For this effort the input layer has 9 nodes and the middle layer has 4

nodes which equates to 36 weights or to a training set requirement of between 180 and 360 examples. For this effort the amount of time required to gather data for one drill can vary between 2 and 6 weeks. Therefore, the amount of time required for a minimum set is 360 weeks or approximately 7 years. This does not include the requirements for a test set with which to challenge the trained network. The current effort does have viable data on 23 new drills; 21 from manufacturer "A" and two from manufacturer "B." The impact of the number of examples in the training set was tested with data from this set, primarily from the 21 manufacturers of "A" drills. The results are shown in Table 14.0.

TABLE 14.0

IMPACT ON ACCURACY OF NUMBER OF EXAMPLES IN TRAINING SET
AVAILABLE MANUFACTURER "A" DRILLS = 21

NUMBER OF EXAMPLES IN TRAINING SET	NUMBER OF EXAMPLES IN TEST SET	RMSE TRAINING SET SET	RMSE TEST	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
13	8	12.64	109.64	13	0
14	7	8.96	114.33	14	1
15	6	7.20	117.80	15	1
16	5	8.38	101.2	16	1
17	4	15.68	89.44	13	0
18	3	10.51	78.20	17	1
19	2	8.80	70.80	18	0
20	1	8.32	65.1	20	0
21	0	8.84	N/A	21	N/A

The neural networks are capable of learning the specific knowledge contained in the training set but problems occur in applying this specific knowledge to the general problem set. However, it is possible that a more accurate network can be trained with something less than 180 examples.

(7) Mixing Drills From Different Manufacturers:

Drills from two manufacturers were used in this effort. However, the number of drills from each manufacturer was not equal, only 2 of the new drills were from manufacturer "B." Because of this situation it is possible to test a neural network capability to transfer knowledge learned from a set of drills from one manufacturer to drills from another manufacturer. Another possibility is to mix the drills into the same training set. The set of new drills available for training and testing a neural network consisted of 21 from manufacturer "A" and two from manufacturer "B". The manufacturer "B" drills are test sequence

numbers 11 and 12. It is pointed out that the descriptive statistics for these two drills are almost identical and in addition the difference in performance was one workpiece, number 11 completed 28 and number 12 completed 29 workpieces. Because the available data covers a tool life span of from 139.5 inches to 474.3 inches the criteria was setup that if a forecast is greater than 474.3 then it is set at 474.3 and if it is less than 139.5 it is set at this value. Overestimates are shown as negatives and underestimates as positives. The results are shown in Table 15.0

TABLE 15.0

IMPACT OF DIFFERENT DRILL MANUFACTURERS

NUMBER OF EXAMPLES IN TRAINING SET	NUMBER OF EXAMPLES IN TEST SET	RMSE TRAINING SET	RMSE TEST SET	ERROR TS 11	ERROR TS 12
13*	8*	12.64*	109.64*	-213.9	111.6
14	7	8.96	114.33	-213.9	65.1
15	6	7.20	117.80	-213.9	120.9
16	5	8.38	101.2	-213.9	18.6
17	4	15.68	89.44	-213.9	55.8
18	3	10.51	78.20	-213.9	55.8
19	2	8.80	70.80	-213.9	130.2
20	1	8.32	65.1	-213.9	55.8
21	0	8.84	N/A	-213.9	93.0
	TRAINING SET INCLUDE MANUFACTURER 'B' DRILLS				
22**	1	14.79****	N/A	18.6	9.3
23***	0	11.66****	N/A	0	-27.9

* TRAINING SET MANUFACTURER 'A' DRILLS ONLY
** TRAINING SET INCLUDES MANUFACTURER 'B' TS11
*** TRAINING SET INCLUDES MANUFACTURER 'B' TS11 AND TS12
****RMSE IS FOR 21 MANUFACTURER 'A' DRILLS

These results indicate that a network trained on drills from one manufacturer cannot be used to forecast life for drills from another producer. However, they also indicate, results shown in entry lines 22 and 23 of the table, that mixing manufacturer in the training set enables a network to handle both producers. These conclusions are tentative since only two drills are available from manufacturer 'B.'

(8) Alternative Methods for Forcasting Tool Life:

There are alternative methods for calculating tool life, these are: (1) forecast total wear and constant wear rate and the quotient yields a forecast of total inches drilled; (2) determine a standard total wear, mean total wear, forecast the constant wear rate, again the quotient yields a forecast of total inches; (3) normalize all experimental inches drilled data to the average total wear and forecast this normalized value. For this set of experiments the training set was reduced from 15 to 14 examples. This is due to the fact that one of the examples contained in the previous training set was missing the data for lip wear. The normalized values for the second alternative are shown in Table 16.0 and the results for all alternatives are shown in Tables 17.0 - 19.0. The first line in each of these tables contains the results of a direct forecast as a means of comparing the alternatives.

TABLE 16.0

NORMALIZED TOOL LIFE DATA
NORMALIZED TO A TOTAL WEAR OF .29MM

DRILL TEST SEQUENCE	ACTUAL WORKPIECES COMPLETED	NORMALIZED WORKPIECES	DIFFERENCE
80	15	22	+7
67	17	15	-2
10	18	25	+7
62	21	22	+1
1	22	20	-2
9	23	25	+2
63	22	26	+4
28	26	24	-2
6	26	21	-5
79	26	27	+1
81	26	23	-1
27	28	29	+1
13	30	28	-2
33	31	30	-1
38	33	32	-1
71	34	35	+1
61	37	35	-2
83	35	39	+4
20	43	41	-2
17	48	43	-5
91	50	48	-2
58	51	42	-9
11*	28	29	+1
12*	29	30	+1

TABLE 17.0

RESULTS ALTERNATIVE FORECASTING METHODS
FIRST ALTERNATIVE-FORECAST BOTH TOTAL WEAR AND CONSTANT WEAR RATE

	RMSE TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
DIRECT FORECAST	7.20	117.80	15	1
TOTAL WEAR	.005MM	.08MM	N/A	N/A
WEAR RATE	.000029MM/INCH	.000255MM/INCH	N/A	N/A
TOTAL INCHES	8.96	127.2	14	1

N/A Not Applicable.

TABLE 18.0

RESULTS ALTERNATIVE FORECASTING METHODS
SECOND ALTERNATIVE-FORECAST TOTAL NORMALIZED TOOL LIFE

	RMSE TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
DIRECT FORECAST	7.20	117.80	15	1
TOTAL INCHES	10.54	92.8	13	1

TABLE 19.0

RESULTS ALTERNATIVE FORECASTING METHODS
THIRD ALTERNATIVE-FORECAST CONSTANT WEAR RATE & USE WITH AVERAGE TOTAL WEAR

	RMSE TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
DIRECT FORECAST	7.20	117.80	15	1
TOTAL INCHES	43.2	141.4	7	2

None of these alternatives is as accurate as forecasting total inches directly, which had an RMSE for the training set of 7.2 and the test set of 117.8.

Another possible method of forecasting total inches directly is to use input data windows and average the forecast for the windows to derive a final forecast. This approach was tried for input values of 6, 7, 8, and 9 thrust values. For example for a window of six values the first forecast would use values from workpieces 1 - 6, the second 2 - 7, the third 3 - 8 and the fourth 4 - 9. However, the 6 element window would only train for the 1-6 and 2-7 windows. The results are shown in Table 20.0. Method A in the table is the 6 element window, it used values for 1-6 and 2-7. Method B is the 7 element window it uses values for 1-7 and 2-8. Method C is the 7 element window it uses values for 1-7, 2-8, and 3-9. Method D is also for the 7 element window and it is based on the average for the first two windows and then the results of the third window are added to the average and divided by 2. Method E is for the 8 element window 1-8 and 2-9. The STD is the current standard method forecasting total inches directly using nine input values.

TABLE 20.0

WINDOWING INPUT DATA

METHOD	RMSE TRAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
A	9.6	79.3	15	1
B	9.9	105.8	15	1
C	12.4	77.0	14	1
D	13.8	72.4	13	1
E	10.8	96.3	15	0
STD	7.2	117.8	15	1

With respect to windowing is there one window that results in a more accurate neural network? The data is shown in Table 21.0 for windows with 6-9 elements.

TABLE 21.0

EFFECTS ON WINDOW LOCATION

WINDOW SIZE	ELEMENTS IN WINDOW	RMSE RAINING SET	RMSE TEST SET	NUMBER OF TRAINING SET FORECASTS WITHIN TWO WORKPIECES	NUMBER OF TEST SET FORECASTS WITHIN TWO WORKPIECES
6	1 - 6	15.74	93.7	14	2
6	2 - 7	11.00	119.3	14	0
7	1 - 7	11.00	83.1	14	1
7	2 - 8	9.90	105.8	15	1
7	3 - 9	12.48	76.9	14	1
8	1 - 8	12.24	75.46	14	0
8	2 - 9	10.74	96.27	15	0
9	1 - 9	7.20	117.8	15	1

These results indicate that a neural network doesn't need the value from the first workpiece. But it does need the one from the second. It also shows that starting the window at the third workpiece is not a good idea. It is possible that the first value represents a wear in period or some other phenomena and that this phenomena is over by the second workpiece.

(9) Training Set Patterns:

Within the tool lifetime data there are patterns; 3 tools drilled 204.6 inches, 4 tools drilled 241.8 inches, and 7 tools had a total wear of .31mm. The question is; can these patterns be employed to assign examples to the training set and the test set and thereby improve the capability of the network? Table 22.0 contains the data for the 3 tool pattern, Table 23.0 contains the data for the 4 tool pattern and Table 24.0 contains the data for the 7 tool pattern. With respect to this last table, data for 6 tools is shown because one tool is missing thrust values.

TABLE 22.0

PATTERN IMPACT ON NETWORK ACCURACY

NUMBER OF TRAINING SET EXAMPLES	NUMBER OF TEST SET EXAMPLES	RMSE TRAINING SET	RMSE TEST SET	ERROR FOR DRILL 1	ERROR FOR DRILL 26	ERROR FOR DRILL 63
13	8	12.64	109.6	204.6	9.3*	-46.5
14	7	8.96	114.3	-223.2	9.3*	55.8
15	6	7.2	117.8	0*	0*	-9.3
16	5	8.4	101.2	9.3*	-9.3*	65.1
17	4	15.68	89.4	9.3*	9.3*	65.1
18	3	10.51	78.2	9.3*	0*	0*

* CONTAINED IN TRAINING SET
NEGATIVE VALUE IS AN OVERESTIMATE
POSITIVE VALUE IS AN UNDERESTIMATE

TABLE 23.0

PATTERN IMPACT ON NETWORK ACCURACY

NUMBER OF TRAINING SET EXAMPLES	NUMBER OF TEST SET EXAMPLES	RMSE TRAINING SET	RMSE TEST SET	ERROR FOR DRILL 6	ERROR FOR DRILL 28	ERROR FOR DRILL 79	ERROR FOR DRILL 81
13	8	12.64	109.6	74.4	46.5	18.6*	-130.2
14	7	8.96	114.3	74.4	65.1	0*	-176.7
15	6	7.2	117.8	-37.2	102.3	0*	-186.0
16	5	8.4	101.2	46.5	-18.6	18.6*	-9.3*
17	4	15.68	89.4	65.1	-28.2	9.3*	18.6*
18	3	10.51	78.2	-37.2	0	9.3*	-27.9*
19	2	8.8	70.8	93.0	-37.2	9.3*	0*
20	1	8.32	65.1	0*	-65.1	18.6*	-18.6*
21	0	8.84	9.3*	-9.3*	18.6*	0*	0*

* CONTAINED IN TRAINING SET
NEGATIVE VALUE IS AN OVERESTIMATE
POSITIVE VALUE IS AN UNDERESTIMATE

TABLE 24.0

PATTERN IMPACT ON NETWORK ACCURACY

NUMBER OF TRNG SET EXAMPLES	NUMBER OF TEST SET EXAMPLES	RMSE TRNG SET	RMSE TEST SET	ERROR FOR DRILL 1	ERROR FOR DRILL 13	ERROR FOR DRILL 20	ERROR FOR DRILL 28	ERROR FOR DRILL 67	ERROR FOR DRILL 91
13	8	12.64	109.6	-204.6	0*	18.6*	46.5	-120.9	18.6*
14	7	8.96	114.3	-223.2	9.3*	-18.6*	65.1	0*	-9.3*
15	6	7.2	117.8	0*	9.3*	-18.6*	102.3	0*	9.3*
16	5	8.4	101.2	3*	0*	9.3*	-18.6	0*	0*
17	4	15.68	89.4	3*	27.9*	27.9*	-37.2	9.3*	-9.3*
18	3	10.51	78.2	9.3*	-9.3*	9.3*	0	-9.3*	-9.3*
19	2	8.8	70.8	9.3*	0*	9.3*	-37.2	0*	0*
20	1	8.32	65.1	0*	9.3*	0*	-65.1	-9.3*	-9.3*
21	0	8.84		9.3*	9.3*	9.3*	-9.3*	9.3*	0*

* CONTAINED IN TRAINING SET
NEGATIVE VALUE IS AN OVERESTIMATE
POSITIVE VALUE IS AN UNDERESTIMATE

The data in these three tables shows that selecting training examples based on some common criteria is not sufficient to improve the accuracy of the network with respect to other drills within the same pattern. The data does show that there is an interaction between these pattern sets and examples that do not belong to the set. This is shown by a decrease in some of the errors when none member examples are added to the training set. The results also indicate that total inches drilled is a better criteria than total wear.

(10) New Drills Vs. Reground Drills:

Within the total data set there are subsets, these are defined in Table 25.0

TABLE 25.0

DATA SUBSET DEFINITION

DRILL CONDITION	DRILL MFGR	DRILL GRIND	TITANIUM NITRIDE COATING	STRESS RELIEVED
NEW	A	CONV*	Y	Y
NEW	B	CONV	Y	Y
REGROUND	A	CONV	Y	N
REGROUND	A	CONV	N	Y
REGROUND	A	CONV	N	N
REGROUND	B	CONV	Y	N
REGROUND	B	CONV	N	N
REGROUND	A	FOUR*	Y	N
REGROUND	A	FOUR	N	N
REGROUND	A	HELI*	N	N

CONV = CONVENTIONAL GRIND
FOUR = FOUR FACET GRIND
HELI = HELICAL GRIND

It is possible that one neural network would have the capability to handle all of these different possibilities. The new drill work has shown that a network can handle variations in certain parameters (not different manufacturers) so the question becomes can a neural network handle new and reground drills. The results of this effort are shown in Table 26.0.

TABLE 26.0

IMPACT OF NEW AND REGROUND DRILLS ON ACCURACY

TRAINING SET	TEST SET	RMSE TRNG SET	RMSE "A" CONV	RMSE "B" CONV	RMSE "A + B" CONV	RMSE "A" FOUR	RMSE "A" NEW
"A" NEW DRILLS	REGROUND CONV AND FOUR	19.5	92.5	132.2	102.7	203.4	19.5
"A + B" REGROUND CONV	"A" NEW AND REGROUND FOUR	24.0	22.2	29.4	24.0	113.1	189.8
"A" FOUR	"A" NEW AND "A + B" REGROUND CONV	13.6	124.0	29.0	110.2	13.6	132.2

In addition to these training sets several others were tried; new drills and conventional grind reground drills, new drills and four facet grind reground drills, conventional and four facet reground drills. These sets failed in training viable neural networks. During training with these sets the training criteria of .05 could not be achieved, in fact the best that could be achieved was .360.

The results shown in Table 26.0 indicate that there is a difference between new and reground drills, even if the grind is identical and both sets of drills are from the same manufacturer. The results for the new drill neural network indicate that regrinding has not removed the difference between manufacturer "A" and manufacturer "B" conventional grind drills as shown by RMSE values of 92.5 for the "A" drills and 132.2 for the "B" drills. The results indicate that the four facet regrind has completely changed the drills, the RMSE for the four facet case is almost twice the value for the conventional grind case, 102.7 to 203.4.

(11) Regrinding and Recoating:

A few of the reground drills were also recoated with Titanium Nitride; two manufacturer "A" conventional grind, one manufacturer "B" conventional grind and three manufacturer "A" four facet grind. The one of interest of course is the manufacturer "A" conventional grind because this is as close to new as can be achieved. The question is did the network trained on new drills consider these to be new drills. The results are

mixed. For one drill the actual error was zero and for the other drill it was an underestimate of 177.4 inches. For the manufacturer "B" conventional reground drill the error was an underestimate of 111.6. This could be further evidence that the reground drills do not perform in the same manner as new drills.

4. DISCUSSION:

Three sets of experimental data were available; new drills-conventional grind-, reground-conventional grind drills-, and reground-four facet grind drills, but, most of the investigations used the new drill data because more new drill data was available and the regrinding operation added another variable.

Within the new drills category some of the drills in addition to being coated with Titanium Nitride were also given additional treatment namely; cryogenic treatment (-300 F) or ion implantation. Therefore, within this category the drills could be further divided into untreated, cryogenically treated or ion implantation.

The neural networks for new and reground drills have nine input nodes, four middle layer nodes and one output node. All of the networks have been trained on problems defined by the average thrust values per workpiece and the output is in total inches drilled. The thrust values are measured as a percentage of the total output that the motor is capable of supplying. Each workpiece has four two inches holes and two additional blind holes that equal an additional 1.9 inches or each workpiece is equivalent to 9.3 inches of metal drilled.

For new and reground drills equation (1) scales the thrust values so that they are between .1 and .9.

(1) SCALED = ((ACTUAL THRUST - MINIMUM THRUST).8 / RANGE) + .1

= ((ACTUAL THRUST - .106).8/.075) + .1

For new drill equation (2) converts the scaled output values to total inches, equation (3) is for reground conventional point drills, and equation (4) is for reground four facet drills.

(2) ACTUAL = MINIMUM ACTUAL VALUE + (SCALED FORECAST -.1)RANGE/.8

= 139.5 + (SCALED FORECAST - .1)334.8/.8

(3) = 93 + (SCALED FORECAST - .1)260.4/.8

(4) = 102.3 + (SCALED FORECAST - .1)353.4/.8

The following conditions also were applied to the forecast for new drills the conditions are: if the forecast is less than 139.4 inches set the forecast to 139.4; if the forecast is greater than 474.3 inches set the forecast to 474.3 inches. For reground conventional grind drills the conditions are: if the forecast is less than 93 inches set the forecast at 93 inches; if the forecast is greater than 353.4 inches set the forecast at 353.4 inches. For reground four facet grind drills the conditions: if the forecast is less than 102.3 inches set the forecast at 102.3; if the forecast is greater than 455.7 inches set the forecast at 455.7.

The first attempts at developing a neural network with the capability to forecast tool life centered around using static parameter values to define the problem; point angle, relief angle, chisel edge length, web thickness, ratio. Predicting performance based on these parameters would have made the problem trivial. However, the network did not perform. The values for the first workpiece for specific energy thrust were added to further define the problem. Then the thrust or specific energy values for the first five workpieces were added to the static variables. These attempts proved fruitless. The use of static variables was discontinued and focus was placed on using thrust and specific energy and variations such as smoothed values and first difference values. The final decision was to use average thrustvalues for the first 9 workpieces as the independent variables. But even here the network did not achieve the goal of a forecast within plus or minus two workpieces when challenged with unknown drill data. However, this might be the result of not enough training examples, only 21 drills from one manufacturer and 2 drills from another manufacturer were available for the new drill set. However, the networks could learn to differentiate the drills in the training set even though the drills were treated and untreated.

The difference in manufacturers was tested. This was accomplished by training the network with drills from one manufacturer and testing it with drills from the other. In most cases the forecasting error was very large. However, when the drills were mixed within the training set and the network was challenged with the training set the addition of the alien drills did not impact the accuracy of the network with respect to the other drills. It seems that the network was able to accommodate the two different manufacturers.

A few of the reground drills were also recoated with Titanium Nitride, it was postulated that this would allow them to perform as a new drill. This was tested by training a network with new drills and then challenging the trained network with these reground recoated drills. The forecasting error was equivalent to those drills that were just reground. The regrinding recoating process does not result in a new drill. It results in a better performing reground drill. A network trained on new drills cannot be used to forecast reground drills and networks

trained on reground drills cannot be used to forecast new drills. For reground drills and probably new drills the grind has to be the same. A network trained on conventional grind drills cannot be used to forecast four facet drills and vice-versa.

Even though the network did not achieve the goal of forecasting unknown challenge drills within plus or minus two workpieces, the forecasting error decreased as the number of examples in the training set increased. This indicates that the number of training set examples is not sufficient.

5. CONCLUSIONS:

a. Utilization of neural networks to forecast twist drill lifetime is feasible.

b. As the investigations into different manufacturers indicate the forecasting capability might not be applicable to the general situation. The forecasting capability would be limited to a specific drill workpiece combination. If the drill or workpiece is changed the network might have to be retrained.

c. The best improver of drill performance is to coat the drills with Titanium Nitride.

d. Average thrust values are the chosen method for problem definition.

e. Smoothing average thrust values or specific energy values increases the difficulty of training a neural network.

f. First difference values loses more of the information and increases the difficulty of training a network.

6. RECOMMENDATIONS:

a. Continue the effort to develop a neural network capable of forecasting tool life. Incorporating new data being generated by the experimental program.

b. Determine if the forecasting capability is only applicable to this drill workpiece combination or can it be generalized to other drills, workpieces, drill workpiece combinations.

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